OPTIMAL PARAMETERS OF SUPPOR VECTOR MACHINE FOR CLASSIFICATION OF MULTISPECTRAL BRAIN MRI

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Abstract

Support vector machine (SVM) has been widely used as a powerful tool for classification problem arising from various fields and shown that the parameters are critical in the performance of SVM [1]. However, the same parameters are not suitable for all classification problems. In this paper, numerical results show that the performance of SVM with optimal parameters is significant difference to empirical parameters. In addition, we recommend independent component analysis (ICA) method as the pre-processing step to get the robust performance of SVM classification problems in brain MRI.

Introduction

Support vector machine (SVM), a new learning algorithm for classification, has been designed using a small set of training data and subsequently refined by actively learning for operating satisfactorily with data outside [2]. The technique has been promising for quantitative volumetric analysis of human brain MRI. However, some important issues have not been addressed for accurate quantification of brain MRI, such as what're the suitable kernel or optimal parameters, and the margin of the soft margin. In this paper, we tried to investigate the feasibility of this classification method and also to optimize the model parameters for volume quantification of brain MRI.

Materials and Methods

The synthetic brain images available from McGill University, Montreal, Canada (available at www.bic.mni.mcgill.ca/brainweb/) were used allowing reproduce our experiments. Multispectral data of axial T1, T2, and proton density MR brain images [with 5-mm section thickness, 0% noise, and 0% intensity non-uniformity (INU)] were analyzed to test the performance of the SVM method .

SVM

SVM is a useful technique for data classification. The performance of SVM algorithm closely depends on the kernel function and their corresponding parameters. The most widely used kernel functions includes linear function, polynomial function, radial basis function (RBF) and sigmoid function. In this paper, we choice the RBF kernel to test our experiments because the linear kernel is a special case of RBF kernel; the polynomial kernel has more hyperparameters than the RBF kernel, and the sigmoid kernel is not valid (i.e. not the inner product of two vectors) under some parameters [4]. In addition, the advantages of SVM with RBF kernel are less numerical difficulties and good performance in other literatures [4]. A learning algorithm, grid search method, was used to select an optimal parameter of SVM. The results were compared with those acquired by using an empirical parameter, usually applied in other classification experiments.

ICA+SVM

Recently, a new application of independent component analysis (ICA), a spectral domain-based approach, was investigated to perform in multispectral MR image analysis for separating tissues with different relaxation characteristics of gray and white matter[5]. We also used SVM as a post ICA processing technique to classify CSF, GM and WM.

Performance Evaluation

The Tanimoto index was measured to statistically evaluate the results of the GM, WM and lesion volumes with the ground truth data of the synthetic brain images, defined as

$$\frac{n_{X\cap Y}}{n_X + n_Y - n_{X\cap Y}} = \frac{n_{X\cap Y}}{n_{X\cup Y}}$$

where X and Y are two data sets, n_X, n_Y, $n_{X\cap Y}$ and $n_{X\cup Y}$ are the cardinalities (number of the elements) of X and Y, respectively. *Tanimoto* index = 0 means that both data sets are completely different and *Tanimoto* index = 1 means that both data sets are the same.

Result

Our results demonstrated that with the optimal parameters SVM method could perform better classification of brain components than that with empirical parameters, as shown in Figure 1-3. The *Tanimoto* indices of GM, WM and CSF classification by SVM with optimal parameters were also higher than those with empirical parameters. By coupling ICA with SVM there was no significant difference of the *Tanimoto* indices between using the optimal and empirical parameters.

A summary of the test data evaluation for empirical and optimization parameters (grid-search method) is shown in Table 1. All performance measures were separately evaluated (with 95% confidence intervals) for empirical and optimization parameter.

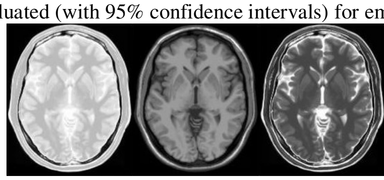

Figure1. Three synthetic MR images, from left to right are PDWI, T1WI, and T2WI. They are used to evaluate the performance of SVM with optimal parameters or not.

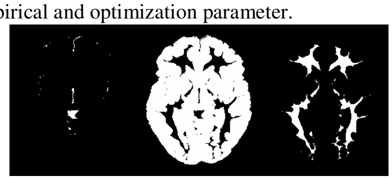

Figure 2. SVM with a set of empirical parameters classified the synthetic MR images. The cost parameter (C) and RBF parameter (γ) are equal to 1 and 0.5 respectively.

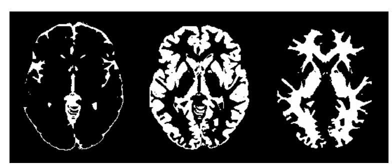

Figure 3. SVM with a set of optimal parameters classified the synthetic MR images. The optimal parameter sets (C, γ) were found by grid search method and equal to 0.03125 and 4 respectively.

Conclusion

In this paper, we demonstrated that some parameters would significantly impact the performance of SVM in brain classification. Better classification and quantification of brain MRI would be achiable with "optimal" parameters that that with "empirical" parameters.However, as coupled with ICA, SVM method would be robust in brain MRI classification.

Table 1. Tanimoto index of CSF, GM, WM, and mean by using "SVM" and "ICA+SVM"

		CSF	GM	WM	Mean
SVM	optimal parameters	0.7425	0.8210	0.8652	0.8096[a]
	empirical parameters	0.0771	0.4913	0.3372	0.3019
ICA+SVM	optimal parameters	0.7886	0.8505	0.9012	0.8468[b]
	empirical parameters	0.7011	0.8400	0.8936	0.8116

[a]: vs "SVM" with the empirical parameters (p value < 0.05)
[b]: vs "ICA+SVM" with the empirical parameters (p value > 0.05)

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